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Neural Network Training on Human Body Core Temperature Data

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ABSTRACT

A multi-layer Adaptive Linear Element neural network computer program was trained with back-propagation on physiological response data from nine subjects walking on a treadmill in two simulated tropical environments. The 100 minute end-point body core temperatures calculated were compared to the measured responses. It was found that although correlation was low and simultaneous high specificity and sensitivity were not displayed, the results were comparable to the predictions from an established human thermal response prediction programme for these subjects. It is concluded that the neural network modelling technique has merit in this field and should be explored further as more data become available.

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Executive Summary

Rapid advancements in computer technology have provided opportunities for biomedical researchers to develop sophisticated computer models for simulation of physiological responses under a wide range of environmental conditions. Of particular military and industrial relevance would be a simulation of human thermoregulation designed specifically to forecast temperature changes within the body, as well as other critical physiological variables to indicate heat strain. The availability of these simulation tools would provide a distinct tactical advantage for military operations in tropical environments. The ability to predict levels of heat strain would allow military planners to develop appropriate heat stress management strategies by optimising the work load for soldiers, resulting in the minimisation of heat casualties and reduced demand on medical logistics. Such tools have been applied in many UN peacekeeping missions by the US military and the outcomes were a general reduction in heat casualties.

The development of empirical algorithms for a computer model to simulate experimentally measured data requires the selection of mathematical equations relevant to the thermoregulatory mechanisms of the body. These equations are refined by reiterated regression analysis until the prediction errors cannot be further minimised. In contrast, a neural networking technique starts with sets of input parameters, the corresponding sets of output results and a large matrix of arbitrarily initialised numbers. To 'train' the network, each set of input parameters is used to calculate one set of output values, which will have some errors. A portion of the output errors is then fed back into the network (back propagated) to adjust the values in the matrix. This process is repeated until the errors cannot be further reduced. The major difference from the regression technique is that the requirement for advance knowledge of the nature of the relationships between input and output is minimal. The matrix, after training, can be used to generate outputs from parameters which were not part of the training process.

This study describes the construction of a neural network program and the training of its matrices on experimental data obtained during a laboratory study with soldiers exercising in environmental chambers under two different conditions similar to typical Pilbara and Townsville weather conditions. The predictions from this program yielded a 'fit' to the experimental data comparable to the USARIEM heat strain predictive program. It is concluded that the application of neural networking may have potential to provide a capability to predict physiological responses in military personnel.

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Peter Sanders started at AMRL in 1966 (then DSL) as a laboratory assistant in Fuels and Lubricants section and subsequently held positions in Explosives Testing, Explosives Research and Fuels Research areas. He graduated in Melbourne in 1977 as a Bachelor of Applied Science (Applied Chemistry) from Phillip Institute - RMIT with the aid of a Final Year Scholoarship awarded by Dept. of Defence. He successfully completed a Graduate Diploma in Computer Science (Melbourne University) in 1990 and has since worked in Personnel Protection and Performance on computer modelling of various aspects of defence against unconventional weopons and modelling of human physiological responses to thermal stress.

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Tony Lau graduated in Hong Kong in 1979 in Biology and Biochemistry and obtained his M.Phil in environmental biology in 1981. Supported by a Croucher Foundation Scholarship (HK), he studied environmental toxicology at Melbourne University and was awarded a Ph.D. degree in 1987. After a short spell of employment as a senior chemist with Unipath Pathology Laboratory, he joined AMRL in 1985 and conducted pharmacological studies leading to improved prophylaxis and therapy of nerve agents. He is currently a Senior Research Scientist involved in environmental physiology research and he is the deputy leader of the Focus Area in Environmental Physiology and Nutrition of the Human Factors Hub.

Contents

1. Introduction

Computer programs have been developed over many years for simulation of physiological responses to exercise under differing conditions (Berlin, Stroschein and Goldman, 1975). Of particular relevance to the Australian Defence Force (ADF) is the ability of these programs to predict physiological strain of soldiers operating in Northern Australia. An empirical heat strain computer program developed by the US Army Research Institute of Environmental Medicine (USARIEM) was used extensively during the Gulf War and during recent US peacekeeping missions in Somalia, Rwanda, Cuba and Haiti. Heat casualties reported in these military operations were substantially fewer than expected. It was suggested that a combination of increased awareness of the risk of thermal stress and the development of preventive guidance based on predictions from the USARIEM computer program had greatly minimised the occurrence of heat injuries (Reardon et. al., 1997).

There are two approaches to developing simulation programs for prediction of thermal strain. The first attempts to build a simulation (or model) of the heat production and thermal transport processes occurring within the body and computes physiological responses to changes in environment and activity. (Stolwijk and Hardy, 1977). An important characteristic of this approach is the incorporation of feedback and other control mechanisms to regulate heat flow. The active systems in the model, such as the dynamics of blood flow, vasoconstriction, vasodilation, sweating and shivering control the passive heat exchange processes.

The second is an empirical approach which focusses on mathematical equations derived from statistical analysis of experimental observations of the relationships between work rate, environmental stress and the clothing ensemble. These equations allow predictions of thermal strain as a function of time only under specified conditions for which the experimental data have been gathered. (Givioni and Goldman, 1972).

The development of suitable algorithms for the implementation of computer programs from statistical analysis of experimental data has required that the researcher first select a mathematical equation with due regard for known theory and then perform successive refinements by repeated regression analysis until an acceptable level of accuracy has been attained. In contrast, a neural networking technique starts off with sets of input parameters, the corresponding sets of output results and a large matrix of arbitrarily initialised numbers. To 'train' the network, each set of input parameters is used to calculate one set of output values, which will be in error to some degree. A portion of the output errors are then fed back into the network (back propagated) to adjust the values in the matrix of numbers. This process is repeated until some measure of success achieves an optimal level. The major difference from the regression technique is that there is no need for advance knowledge of the relationship between input and output. The matrix is then said to be 'trained' on the input data and can be

used to generate or 'generalise' output from parameters which were not part of the training process.

This study describes the construction of such a neural network program and the training of its matrices on experimental data obtained during a laboratory study with soldiers wearing the Disruptive Pattern Combat Uniform (DPCU), the standard Australian Army uniform (Amos and Egglestone, 1995).

2. Mathematical Basis

The neural network method best suited to the production of an arbitrary number of linear outputs from an arbitrary number of linear inputs is called the Adaptive Linear Element (Adaline) with Supervised Back-Propagation as the learning rule (Lippmann, 1987). In this method sets of training data consisting of inputs and the corresponding outputs must be available. The way such an Adaline works is indicated diagrammatically below.

Input Vector	Normalising Vector	Weights Matrix					
I_1	N_1	$W_{1,1}$	$W_{1,2}$	$W_{1,3}$	..	..	$W_{1,m}$
I_2	N_2	$W_{2,1}$	$W_{2,2}$	$W_{2,3}$	..	..	$W_{2,m}$
I_3	N_3	$W_{3,1}$	$W_{3,2}$	$W_{3,3}$	..	..	$W_{3,m}$
|	|	|	|	|	::	::	|
|	|	|	|	|	::	::	|
I_n	N_n	$W_{n,1}$	$W_{n,2}$	$W_{n,3}$	..	..	$W_{n,m}$
	Output Bias Vector →	B_1	B_2	B_3	..	..	B_m
		|	|	|	::	::	|
	Output Vector →	O_1	O_2	O_3	..	..	O_m

The elements of this diagram consist of a vector [I] of input numbers, a vector [O] of output numbers, the weights matrix [W] and two vectors ([N] and [B]). The only purpose of which is to improve computational accuracy by 'normalising' data values. As a consequence of the way real numbers are stored within a computer, precision decreases as number values diverge from 1.0, therefore the normalising process tends to force all numbers entering into calculations to be as close to 1.0 as possible. Consequently each N_i will approximate the reciprocal of the mean value of all I_i and each B_j will approximate the mean value of all O_j in the training data.

Processing begins by initialising all the weights in the matrix to be approximately 1. Outputs (G) are then calculated (Lippmann, 1987) using an equation similar to the following:

$$G_j = \frac{B_j}{n} \sum_{i=1}^{n} I_i N_i W_{i,j}$$

The generated output values will have some errors. The weights matrix will be adjusted by back-propagating an arbitrarily chosen fraction (F) of this error. The training may have to be repeated several times to enable an optimal value for F to be determined. Each weight then has a new value.

$$\left[W_{i,j} = W_{i,j} (1.0 - \frac{G_j - O_j}{B_j} F) \right]_{i=1,n}^{j=1,m}$$

Simultaneous with this back-propagation, some measures of the error levels are accumulated for later use in determining whether sufficient training has been conducted. This processing is repeated for each of the training sets. One epoch is said to be completed when the entire training data has been processed once. At the end of each epoch, the overall error level for the entire epoch is compared to preceding epochs and decisions about whether to continue training or the need to modify processing constants (such as the back-propagation fraction) are made.

This single-layer Adaline often does not have sufficient complexity for subtle real-world problems, in which case up to three or even four matrices of weights may be employed. In these Multi-Layer Adalines, processing occurs one layer at a time as described above but now the outputs from the first layer become the inputs for the second layer (using a second weights matrix), the outputs from the second layer become the inputs for the third layer and so on. In the Multi-Layer Adaline, the normalisation vectors are not employed between layers as this is unnecessary; they are only needed for the initial inputs and the final outputs.

3. Method

Laboratory trial data on soldiers exercising in the heat were used to train the neural network. Details of the trial objectives and conditions (Amos and Egglestone, 1995) are summarised below:

Nine soldiers from 1st Commando Regiment aged 19 to 26 participated in this trial. Subjects wore the Disruptive Pattern Combat Uniform (DPCU) with undergarments and boots and carried weights of approximately 11 kg. They walked on a motor-driven treadmill, with a slope of 6% at 5 $km.hr^{-1}$ for 100 minutes. Wind speed was set at 1.1 $m.s^{-1}$ and water consumption during the exercise was recorded. Peak metabolic rate was estimated by measuring VO_{2peak} before the trial while the metabolic rate during exercise was also estimated by measuring VO_2 with an open-circuit spirometer. Personal information such as age, body weight and height was measured and recorded before the trial commenced. The rectal temperature, heart rate and area weighted mean skin temperature were measured continuously while the sweat rate was estimated by the weight difference before and after walking. Two sets of experimental conditions were provided for the exercise. For the first, the temperature was set at 30°C and 60% Relative Humidity (RH); the second at 40°C and 30%RH. These two conditions simulate typical climates at Townsville and Pilbara respectively.

A program to implement the Adaline was written in Gnu C++ on a 120MHz Pentium computer running the Gnu Public Licence Unix 'Linux' but the resulting source code is not system dependent. The single-layer Adaline written initially was expanded to two and then three layers as the software matured.
The Adaline was provided with the following inputs:

- Subject details (nude weight, height, length of acclimatisation)
- Clothing properties (insulation, permeability and 'bagginess').
- Environment (ambient temperature and relative humidity, wind speed, terrain difficulty) factors.
- Total metabolic rate (calculated from equation 4, Givioni & Goldman, 1973).

In fact, all of these inputs were the same for all subjects except the personal weight, height details and the calculated specific metabolic rate which depends (in part) on individual body weight under the experimental conditions. The additional inputs were provided against the possible use of the program with other experimental data. The calculated outputs during the training were the 100 minute-by-minute body core temperature measurements.

The written program was set up so that initially 50% of the generalisation stage errors were used to correct the weights matrices until the most significant digit of the RMS collation of the errors had been unchanged for 10 epochs. The error factor was then divided by 10 and the next most significant digit of the RMS error monitored in the same way. This algorithm was repeated a further four times until the RMS error had

become stable to one part in 1,000,000 which required less than 100 epochs or less than two minutes on the computer in use. This level of training accuracy is considerably more than the 0.1C° (0.1 Celcius degree) required to equal the accuracy of experimental data and may be decreased if larger data sets result in long training times.

4. Results and Discussion

Table 1 shows the end-point (100 min) rectal temperature calculated by the generalisation stage of the three-layer Adaline and the measured temperatures from the 1995 AMRL laboratory studies. The measured end-point temperatures varied from 37.6°C to 38.7°C when subjects exercised in 30°C and 60% RH. The calculated values ranged from 38.3°C to 38.7°C. This corresponds to a mean error of 0.3C°. Under warmer and more arid conditions (40°C and 30% RH), the discrepancy between the measured and calculated mean end-point rectal temperature changed to -0.2C°.

Table 1: The Measured and Calculated End-Point (100 minute) Rectal Temperature under Two Simulated Tropical Conditions.

	Environment 30°C and 60% RH		Environment 40°C and 30% RH	
Subjects	Measured Temp (°C)	Calculated Temp (°C)	Measured Temp (°C)	Calculated Temp (°C)
A	38.4_a	38.8_b	38.4	38.2
B	38.3	38.4	38.7	38.4
C	38.7	38.4	39.0_a	38.3_b
D	38.3	38.7	38.5	38.4
E	38.1	38.6	38.5	38.2
F	38.4_a	38.4_b	39.0_a	38.6_b
G	37.6	38.3	nd_a	38.4_b
H	38.2	38.6	38.5	38.6
I	37.9	38.4	38.6	38.5
Mean	38.2	38.5	38.6	38.4

Note: a Because the subject exceeded the experimental safe core temperature threshold (39.0°C) or because of loss of good contact with the rectal temperature probe, a full 100 minute set of measured data are not available in these instances.

b These end-point values were calculated after the network had been trained. The parameter sets for these subjects were not part of the training process hence these points are examples of the predictions that the network is capable of making.

The relationship between the measured and predicted end-point rectal temperature was analysed by a linear regression analysis. The Pearson Correlation coefficients between the measured and predicted rectal temperatures were 0.19 at 30°C and 60%RH and 0.34 at 40°C and 30%RH. These results indicate that a positive but weak correlation

existed between the predicted and the measured rectal temperatures in both experimental conditions.

The accuracy of prediction of Adaline-calculated end-point rectal temperatures can be further evaluated by analysing their Specificity and Sensitivity. The definitions of Sensitivity and Specificity are based on the criterion that a warning will be issued if rectal temperature reaches or exceeds 38.5°C, the level at which some OH & S practitioners accept as an upper safety limit for heat strain for civilians. Specificity is defined as True Negative divided by (False Negative + True Negative)[TN/(FP+TN)], Sensitivity as True Positive divided by (True Positive + False Negative) [TP/(TP+FN)] (Reneau and Bishop 1996). Table 2 shows the resulting specificity and sensitivity values for 100 minute end-point temperatures calculated by the Adaline.

Table 2: Sensitivity and Specificity Values for the Three-Layer Adaline Calculated Rectal Temperatures Adopting an Upper Threshold of 38.5°C

	30°C and 60% RH	40°C and 30% RH
Specificity	0.75	1.0
Sensitivity	0	0.4

A good prediction model would have high Sensitivity and Specificity and high correlation with the measured values. The lack of simultaneous high Specificity and high Sensitivity and the generally low correlation between the measured and predicted values suggests that this neural networking technique has relatively low predictive precision. However, when the above results are compared with those obtained from the original USARIEM program (Lau and Sanders, 1998), it is found that this infant neural networking technique has achieved similar predictive precision to a program which required significant resources to develop. The potential now exists for further experimental data to be examined using this new technique.

5. Conclusions

A neural network computer program was constructed and trained on human body core temperature data obtained in a recent laboratory study of subjects exercising in two tropical conditions. The validity of the calculated core temperatures was tested against the measured core temperatures which were used to train the network. It was found that:

1. The calculated final (100 minutes) rectal temperature had a Root Mean Square error of 0.4 C° in the 30°C/60%RH environment and of 0.2 C° in the 40°C/30%RH environment. The difference between the two environments is not significant.

2. The calculated end-point temperatures did not show high correlation with measured values nor did they display simultaneous high specificity and sensitivity for a threshold core temperature of 38.5°C, suggesting a relatively low prediction accuracy
3. The calculated end-point values showed a marginally higher correlation coefficient and a slight improvement in the sensitivity and specificity than those calculated by the original USARIEM computer program for the same subjects.

It is concluded that the Adaptive Linear Element neural networking technique with Back-Propagation as the learning rule is worthy of further investigation as a tool for the prediction of human physiological responses to thermal stress. A data set of only nine subjects used for this study is insufficient to allow more definite conclusions to be drawn. It is recommended that further evaluation on the validity of the Neural Network program technique should be conducted against larger data sets measured under a variety of experimental conditions.

6. Acknowledgments

The authors would like to thank D.Amos and G.Egglestone for their permission to use the physiological data measured in a laboratory study conducted at AMRL in 1995.

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